COMPARING SPATIAL MEASURES OF THE BUILT ENVIRONMENT

FOR HEALTH RESEARCH

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DEDICATION

I dedicate this thesis to Adriana, without whose love, companionship, and encouragement it would have never been realized, and to my parents for their unquestioning support.

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ABSTRACT

Shawn C. Hoch

COMPARING SPATIAL MEASURES OF THE BUILT ENVIORNMENT FOR HEALTH RESEARCH

Research on the association between health and the built environment often delineates environmental exposure using different spatial forms and distances surrounding points of interest, such as residences or schools. Examples from the literature include Euclidian and network buffers, administrative and census boundaries, and other arbitrary geographies, such as grid cells. There is a lack, however, of reports that describe the justifications or implications for using different methods. This research compares different forms and distances for measuring environmental variables surrounding residential locations in the context of adult walking behavior in Marion County, Indiana. Walkability index and vegetation greenness variables were evaluated within 400-meter, 1-kilometer, and 2-kilometer Euclidian and network buffers, census block groups and tracts, and 805- X 805-meter grid cells. Results of analyses using each of these methods to test walkability and greenness as correlates of self-reported walking behavior were compared. Significant differences were observed in measurements of environmental variables as a function of both size and form. There were also significant differences between spatial measure methods when measuring components of walkability and NDVI. Census geographies, widely used in the public health literature, yielded environmental variable measurements differently than did similarly-sized residence-based measure methods. In logistic regressions, the walkability index did not exhibit a significant relationship with self-reported walking behavior. NDVI exhibited a negative relationship with self-reported walking, although the relationship was reversed and significant when stratifying by residential density.

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INTRODUCTION

Research on health and the built environment often requires delineating relevant space of contextual exposure. This space may include an area surrounding a person's home or other important places in daily life. These delineated areas are used to create measures of environmental exposure in order to study associations between such exposure and health outcomes. The past decade has shown a rapid rise in research aimed at identifying built environment factors that may represent targets for interventions to increase physical activity, promote optimal nutrition, and ultimately prevent obesity and its adverse effects on health. Specific methodological approaches define relevant space using Euclidian and network buffers (Frank, Andresen, and Schmid 2004; Frank *et al.* 2005; Kerr *et al.* 2006; Eid *et al.* 2006; McCormack *et al.* 2006), census geographies (Pearl, Braveman, and Abrams 2001; Morland *et al.* 2002; Saelens *et al.* 2003; Ewing *et al.* 2003), grids overlaid on the study area (Boarnet *et al.* 2006; Forsyth *et al.* 2007), and nearest location comparisons (Burdette and Whitaker 2004; Pearce, Witten, and Bartie 2006; Pearce *et al.* 2006). As a potential indicator of differences between these myriad methods, results of analyses of the relationship between the built environment and health have varied.

As the interdisciplinary literature on health effects of the built environment looks forward, how should researchers frame their decisions regarding measuring relevant space? Papas *et al.* (2007) describes the current body of health research in which, "[t]he wide range of conceptualization and operationalization of measures of the built environment makes it challenging to compare results across studies" (p. 139). In order to address a lack of conceptually- or analytically-informed decisions regarding methods for measuring characteristics of the built environment, this research presents comparisons for walkability and greenness using nine methods for delineating analytic zones: (1) an 805-meter X 805-meter resolution grid, (2-4) 400-meter, 1-kilometer, and 2-kilometer Euclidian buffers, (5-7) 400-meter, 1-kilometer, and 2-kilometer network buffers, (8) census block groups, and (9) census tracts. Tests for significant differences of walkability and greenness measurements among these spatial forms and distances are performed. Each measure and distance is also used in logistic regressions to test associations between a walkability index and greenness with the amount of walking per week among a sample of adults in Marion County, Indiana.

BACKGROUND

While some authors have briefly commented on their decision to use a given delineation of relevant space or compared their spatial analysis methods to those in other work (Frank *et al.* 2005; Eid *et al.* 2006), the literature lacks analytical comparison and criticism of these different methods and their results. One potential source of variation in reported associations of the built environment with health outcomes of interest when considering both distance (e.g., 1-kilometer vs. 2-kilometer buffers) and form (e.g., Euclidian vs. network buffers) is the modifiable areal unit problem (MAUP). Openshaw and Taylor (1979) discussed the effects of different methods of grouping geographies into larger units on the correlation between two variables. They observed that twelve districts could be created by combining Iowa counties in different configurations, producing a range of correlations between the percentages of elderly voters and Republican voters from strongly negative to nearly perfectly positive. Gotway and Young (2002) summarized this and previous research as revealing two issues related to the MAUP: (1) relationships among attributes change as areal units are aggregated or geographically scaled down, and (2) the same relationships also change with alternate aggregations of areal units.

Another potential source of variation among results using different types of geographies could stem from their appropriateness for the given variable. For example, in measuring access to parks and recreational facilities surrounding children's residential locations, Euclidian buffers may better model their walking behavior compared to models that assume movement is constrained to street networks. Likewise, network buffers could more accurately reflect access to more sparse amenities such as supermarkets, especially across longer distances and given barriers to walking such as interstates or lack of sidewalks. Diez Roux (2001) suggests when examining environmental effects on health, definitions of neighborhood should be informed by the research goals and that relevant types and scales of geographies "…may vary according to the processes through which the area effect is hypothesized to operate…" (p. 1785). The question of appropriate methods of measurement is strongly dependent on the way in which people interact with their environment and in the absence of detailed observations, can be tested empirically using spatial information in geographic information systems (GIS).

Spatial Measure Methods Previously Used

Throughout recent advances in health literature focusing on the built environment, thorough discussion of methods concerning scale and definition of relevant space or neighborhood in spatial analysis has been lacking. Because of their national scope, wide range of sociodemographic and other descriptive content, and free access, U.S. Census geographies are commonly used to measure environmental variables in the United States, although the degree to which they represent neighborhood in research on environmental effects on health has been questioned (Coulton *et al.* 2001; Pearce, Witten, and Bartie 2006; Papas *et al.* 2007). Boyle and Willms (1999) demonstrated systematic weaknesses of large administrative boundaries in predicting health outcomes, questioning their utility in study of place effects. The authors compared statistical significance of place effects on self-reported health and well-being in Ontario at public health unit levels (a total of 42 dividing the province based on population) to the same observed in smaller geographic boundaries.

Nevertheless, census geographies have been used to delineate environmental variables in relation to health outcomes in several studies. Pearl, Braveman, and Abrams (2001) examined relationships between birth weight and the socioeconomic characteristics of neighborhoods, which they defined as census block groups. They reported results showing lower birth weight among Blacks and Asians in high-deprivation block groups as similar to those resulting from the use of census tracts, although they presented only results using block groups. Morland, Wing, and Diez Roux (2002) used census tracts as approximations of neighborhoods to investigate counts of food services of different types on dietary behavioral outcomes. Their results showed increased fruit and vegetable intake for each additional supermarket. Saelens *et al.* (2003) also used census tracts to define two neighborhoods within which residents responded to a survey on their perceptions of neighborhood walkability. After defining the neighborhoods as more and less walkable, they analyzed physical activity outcomes using accelerometer data from study participants. Their results supported associations of self-reported walkability of neighborhood with physical activity and overweight. The authors did not specify whether the structure of the survey considered the respondents' perceptions of the extent of their neighborhood.

Ewing *et al.* (2003) used county boundaries and metropolitan areas (groups of contiguous counties) to analyze population density, land-use patterns, and street network design, ultimately creating a "sprawl index" that was used to predict physical activity and BMI. They recognized that county and metropolitan area geographies are coarse in terms of analyzing individuals' neighborhoods and that future research should "hone in on the specific living and working environments of individuals." (p. 56)

In examining activity levels surrounding amenity sites, Lindsey *et al.* (2006) investigated effects of neighborhood characteristics on urban trail traffic at specific points along trails. Neighborhoods were defined as groups of census blocks intersecting or adjacent to street segments within ½-mile network buffers surrounding trail access points. Sociodemographic variables used in the analysis were aggregated by trail segment according to the block groups in which they were nested. Trail use was found to be significantly correlated with neighborhood characteristics. At a finer level of neighborhood analysis, Schootman *et al.* (2006) used census blocks to evaluate relationships between visible physical conditions of the block faces and lower-body functional limitations (LBFLs) of study subjects. Poor neighborhood conditions were found to be associated with LBFLs among middle-aged African Americans.

Neighborhood has also been defined using census variables in health research internationally. Pearce, Witten, and Bartie (2006) and Pearce *et al.* (2006) used meshblocks, the smallest New Zealand census unit designed to include around 100 people, to compare access to health-related community resources across levels of deprivation. Meshblocks were grouped by quintiles of the New Zealand Deprivation Index, derived from nine socioeconomic variables. Access to resources was measured using the population-weighted centroid of meshblocks and network distances to closest facilities.

Parcel data provides cadastral detail at a finer scale than census geographies and has also been introduced in assessments of neighborhood characteristics for health research. Parcels have been used to measure land-use variables, such as land-use mix, as proxies for opportunity for utilitarian walking (Frank, Andresen, and Schmid 2004; Frank *et al.* 2005; Lindsey *et al.* 2006; Forsyth *et al.* 2007), usually assigning results to larger units such as census geographies. Building footprints have also been used to determine the mean offset from streets as a determinant of walkability (Liu and Colbert *et al.* 2007). No studies were found in a review of the literature that employed parcel boundaries or building footprints to define relevant spatial units for analysis of the built environment.

Researchers have also used buffers around geographic coordinates, usually geocoded study subject locations, to delineate relevant space. Such methods are potentially more relevant in describing individual-level environmental exposure than large administrative units given that they produce individual-based spatial units within which to measure. Most GIS software also offers several options in creating buffers: they can be drawn at the distance of choice, nested to form "rings," or snapped to a network to represent distance that can only be traced along a given infrastructure. Frank *et al.* (2005) used 1-kilometer street network buffers surrounding subjects' residences in a study of the effects of the built environment on physical activity. Subject buffers and census block groups were employed in a walkability index for what the authors describe as participant "microenvironments" (Frank *et al.* 2005). They addressed their decision to use network buffers as an attempt to capture the area most accessible for each residence point. Kerr *et al.* (2006) also used 1-kilometer street network buffers to devise the walkability index found in Frank *et al.* (2005) within each buffer, compared results with perceptions of walkability, and analyzed relationships with active commuting to school among children. Objectively measured built environment variables were found to be associated with active commuting. While analysis of the street network surrounding point locations intuitively leads to a more accurate representation of the area accessible by automobile within a given distance in any direction, the authors here frame network buffers as useful specifically in analyzing pedestrian movement, an assumption that has been supported by later work comparing the use of Euclidian and network buffers in assessment of impact of land-use on walking (Oliver, Schuurman, and Hall 2007).

In comparison to network buffers, Euclidian buffers could potentially represent relevant exposure, access to resources, and spaces of opportunity for physical activity where street networks and other features do not present barriers to movement. Euclidian buffers also have the advantage of being more simplistic and therefore more efficient in terms of implementation in GIS. Recent examples of Euclidian, or straight-line buffers, in analysis of the built environment have included neighborhood walkability assessment by McCormack *et al.* (2006) and examination of relationships between urban sprawl and obesity by Eid *et al.* (2006), using 400-meter and 2-mile buffers respectively. Eid *et al.* (2006) presented their use of the 2-mile "disc" as a response to Ewing *et al.*'s (2003) use of counties, which they deemed "very large relative to any sensible definition of a residential neighborhood" (p. 3). Berke *et al.* (2007) employed a previously designed walkability score from the King County, Washington Walkable and Bikable Communities Project to assess effects of the built environment on walking among older persons using 100-, 500-, and 1000-meter Euclidian buffers. The authors reported that smaller buffer sizes were "representative of distances usually traveled on foot," particularly for their target population (p. 488). They also cited earlier works by Moudon and Lee (2003) and Moudon *et al.* (2006) on neighborhood walkability for previous implementation of the 1-kilometer Euclidian buffer.

Considering Distance

As seen in the range of Euclidian and network buffer sizes employed in the literature examining effects of the built environment on physical activity, researchers have yet to reach a consensus regarding appropriate scales at which to assess environmental impact. One-quarter mile, or approximately 400 meters, has been estimated as the typical extent to which adults will walk in environments supportive of walking (Untermann 1984). Average length of walking trips has also been reported as one kilometer (Moudon and Lee 2003). Larger scales may capture degree of attractiveness and conduciveness to walking beyond immediate residential surroundings. In urban environments, distance to public transportation access may also be influential in describing appropriate extent of environmental effects on health (Sjolie and Thuen 2002).

SURVEY RESPONDENT DATA

Marion County Adult Obesity Survey

Data on physical activity, food intake, and prevalence of walking were collected in the Marion County Adult Obesity Needs Assessment Telephone Survey (Marion County Health Department, 2005). The survey was designed to collect information on Marion County, Indiana residents in an effort to provide baseline data for community action and collaboration in reducing overweight. The telephone interview survey was conducted between late February and late July 2005 between the hours of 10:00 A.M. and 9:30 P.M. by the Survey Research Center at Indiana University-Purdue University Indianapolis on behalf of the Marion County Health Department. Interviewers conducted surveys with 4,784 respondents, which represent 34.1% of potential respondents contacted. Interviews were approximately evenly distributed by month across the survey time period in order to allow studying seasonal variations in certain response items such as those related to physical activity. While collecting responses, over-sampling was used in order to produce a representative sample containing at least 200 respondents of each gender from non-Latino Caucasian, African American, and Latino groups. Respondents not residing in Marion County, pregnant women, and respondents under the age of 18 were excluded. For respondents who preferred to conduct the survey in Spanish, a follow-up survey was conducted when a Spanish-speaking interviewer was available.

The survey instrument consisted of seventy-nine questions arranged by topics including opportunity for and amount of physical activity, food availability, eating habits, measured and perceived weight, health status, and demographic information. Respondent demographic information available in the survey included age, gender, race, educational attainment, and annual household income relative to the federal poverty level. The content of the questionnaire was developed by the Marion County Health Department in conjunction with other organizations such as a community advisory group and the Indiana University School of Medicine Department of Family Medicine's Bowen Research Center. Items included were based on those found in other established and widely available instruments such as the Center for Disease Control's Behavioral Risk Factor Surveillance Survey. The study was approved by the Indiana University Institutional Review Board before the survey was administered. Use of survey results in the current study was approved by the Health and Hospital Corporation of Marion County Director of Epidemiology.

Geocoding

Survey respondent records included self-reported nearest street intersections to respondent residences and the FIPS codes for U.S. census tracts within which respondents resided. Census tracts were assigned to each respondent prior to the study by the telephone number data vendor, Survey Sampling International. Analysts at the IUPUI School of Public and Environmental Affairs Center for Urban Policy and the Environment geocoded street intersections as reported in the survey, using census tracts as reference. A street base produced by the Indianapolis Mapping and Geographic Infrastructure System (IMAGIS - www6.indygov.org/imagis/) was used in ArcMap 9.0 (ESRI, Redlands, California) to locate the intersections.

3,499 records (73.1%) were matched successfully using ArcMap's geocoding algorithm. After data cleaning including correcting misspelled street names and considering alternate street names, an additional 180 (3.8%) records successfully geocoded. Remaining records were manually geocoded to intersections or other reference points. For existing intersections not located by the GIS but visible in the street base, records were located manually (N=611). Where respondents provided two streets that did not intersect within their pre-attributed census tract, records were located to a point in the middle of the tract, halfway between the parallel or partially parallel streets (N=197) (Figure 1a). Where respondents provided only one street name, records were located to the point halfway along the portion of that street that transected their census tract (N=165) (Figure 1b). Where respondents provided only one street or two streets which did not transect their census tract, or where intersection information was otherwise incomplete or inaccurate, records were located to the tract centroid (N=131) (Figure 1c).

Figure 1a – Example of Respondent Located Between Parallel Streets.

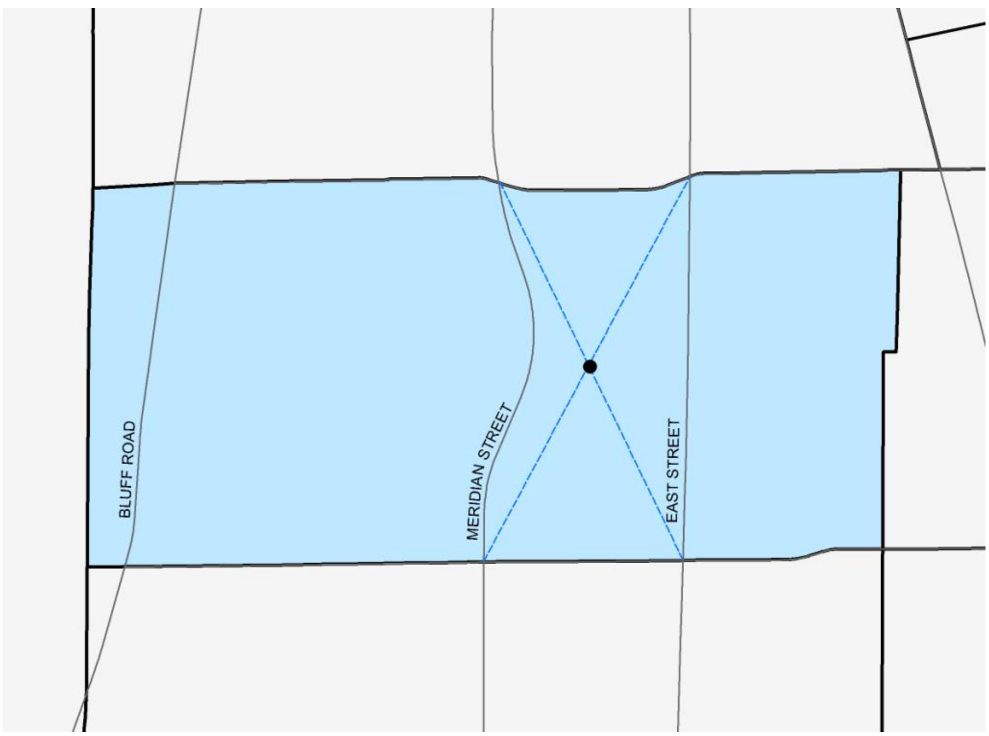


Figure 1b – Example of Respondent Located Along Single Street.

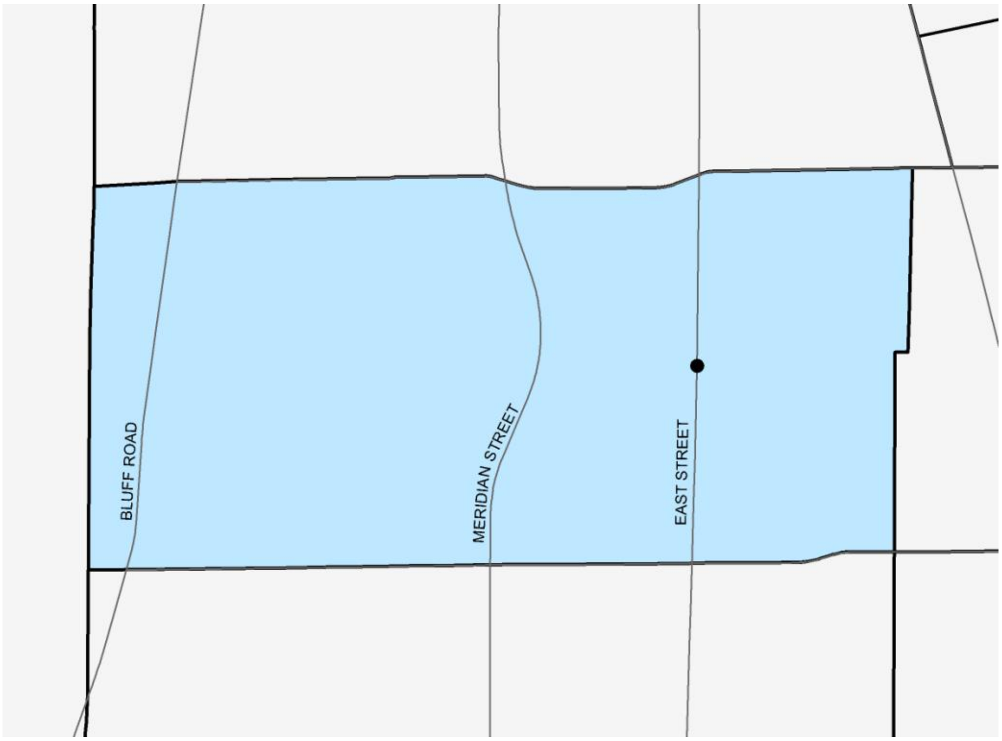
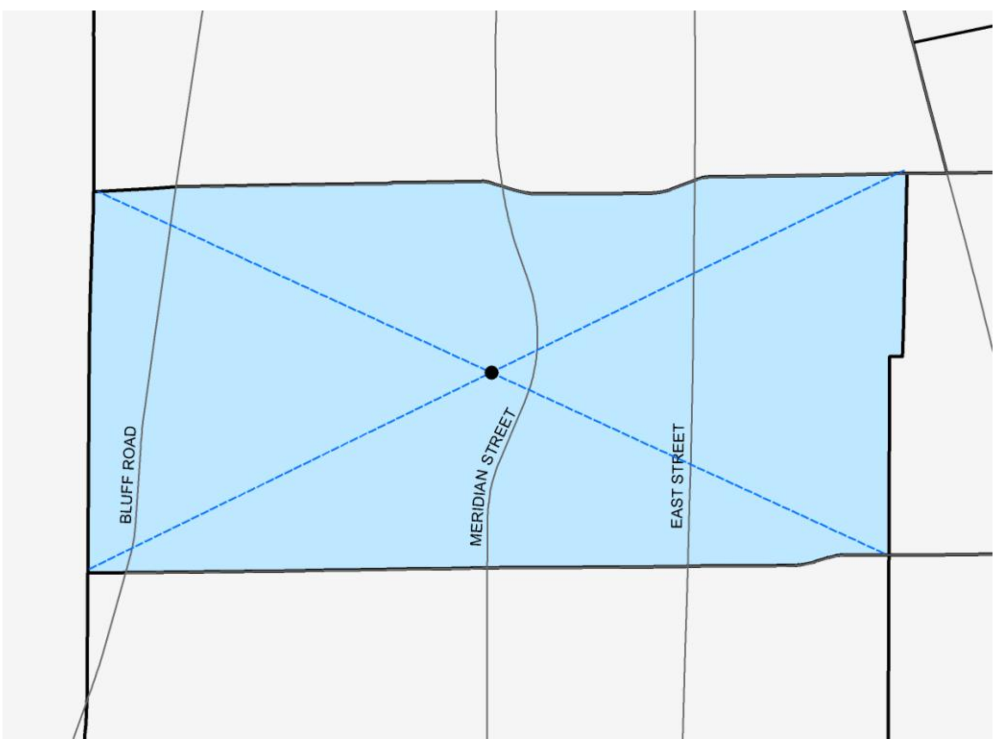


Figure 1c – Example of Respondent Located to Census Tract Centroid.



One record did not have complete intersection information and also lacked an assigned census tract. Eleven records from the resulting geocoded dataset (N=4783) were flagged prior to this study by the Survey Research Center due to errors in respondent variables and were not considered here, resulting in 4,772 geocoded respondent locations.

Delineations of Respondent Environment

Spatial measures were developed such that they were either centered on respondent location (Euclidian and network buffers) or assigned value by virtue of the respondent's location falling anywhere within an arbitrary region (grid cells and census geographies). Grid cells measuring 805 X 805 meters were overlaid on the Marion County study area in a 42 X 41 cell pattern. The grid was overlaid in such a way that all areas within the county boundaries were included in a grid cell. The grid was also oriented in geographic space to minimize the study area coinciding with cells at the edge of the grid (20.8 square miles, or 5.2% of the study area), which would be excluded from analyses due to edge effects. Grid cells in which respondent locations were geocoded were used in comparison of spatial measures. Euclidian and network buffers were generated around each respondent location at distances of 400 meters, 1 kilometer, and 2 kilometers. Because this study focused on walking, street network buffers were not constrained by vehicular traffic restrictions. Network buffers were created using the ArcMap 9.2 Network Analyst extension "Service Area" tool.

Table 1 – Areas or Mean Areas of Spatial Measure Methods.

		Mean Area (Sq Km)	Min	Max	SD
1	400-m Network Buffers	0.261	0.002	0.657	0.065
2	400-m Euclidian Buffers	0.503	0.503	0.503	0.000
3	805-m X 805-m Grid Cells	0.648	0.648	0.648	0.000
4	1-km Network Buffers	1.603	0.119	2.605	0.327
5	Census Block Groups	1.799	0.058	38.109	3.549
6	1-km Euclidian Buffers	3.142	3.142	3.142	0.000
7	Census Tracts	5.103	0.524	44.240	6.533
8	2-km Network Buffers	6.450	0.953	8.763	0.000
9	2-km Euclidian Buffers	12.566	12.566	12.566	0.000

A total of 811 2-kilometer Euclidian buffers (17.0%) of geocoded respondent locations exceeded the study area boundary. Of these location buffers, 263 extended to Hamilton County, Indiana, which had comparable land-use data and a detailed street base. The remaining 2-kilometer respondent location buffers extended into counties for which these data were not available. These respondents, hereafter referred to as “edge residents,” were excluded from the analysis (N=548). Grid cells and street network buffers also exceeding the extent of data availability were excluded when selecting for all those respondents with 2-kilometer Euclidian buffers in this category.

ENVIRONMENTAL VARIABLES

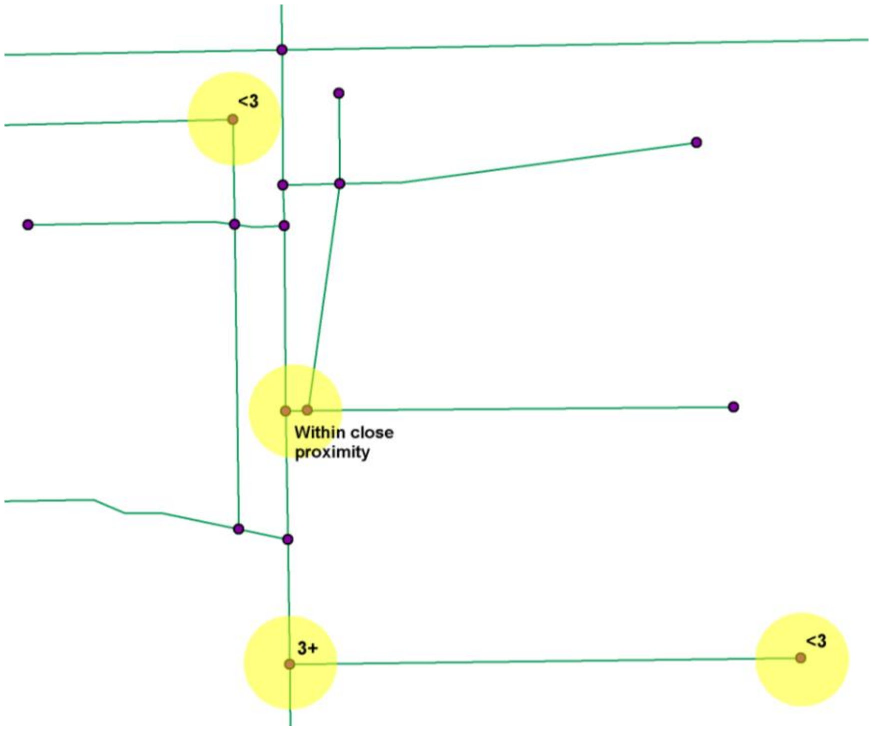
Residential Density

Measurement of residential density was based on household density. Household counts per census block group were derived from 2000 U.S. Census data. Residential land-use polygons were selected from a land-use dataset produced by IMAGIS. The residential land-use polygon layer was intersected with census block group boundaries in order to determine the total area of residential land-use within each block group. Residential density (households per square mile of residential land-use) was then assigned to each census block group and, consequently, to each residential land-use polygon within it.

Street Connectivity

Street network centerline data, also retrieved from IMAGIS, includes street centerlines digitized from current orthophotographs of Marion County. Intersections were derived from the centerline data through the creation of a network dataset using the ArcMap 9.2 Network Analyst extension. The network dataset includes a layer of nodes at the ends of all street segments. Each node was attributed the number of street segments to which it connected in order to determine its valence. For example, a node with a valence of two could represent a point connecting two segments of one street, or a corner where the ends of two streets meet. Such points, while included in GIS network datasets, are not commonly perceived as intersections and could represent curves or bends in streets. Figure 2 displays intersections with a valence less than 3, those with a valence of 3 or higher, and those within close proximity of each other and with a combined valence of 3 or higher.

Figure 2 – Three Different Types of Intersections



Nodes to which more than two segments are connected represent intersections, which have been identified as supportive of physical activity (Dill 2003; Frank, Andresen, and Schmid 2004). Street intersections with a valence greater than two were selected. Where selected intersections were within 10 meters of each other and had a combined valence of 3 or higher, they were dissolved to one intersection at the geometric center of the group of points, following the methods developed in Forsyth *et al.* (2007). After dissolving, street connectivity was defined as the number of intersections (with a valence greater than two) per square mile of land area.

Land-use Mix

Frank *et al.*'s (2005) land-use mix formula was used to derive a land-use mix score for each spatial measure method:

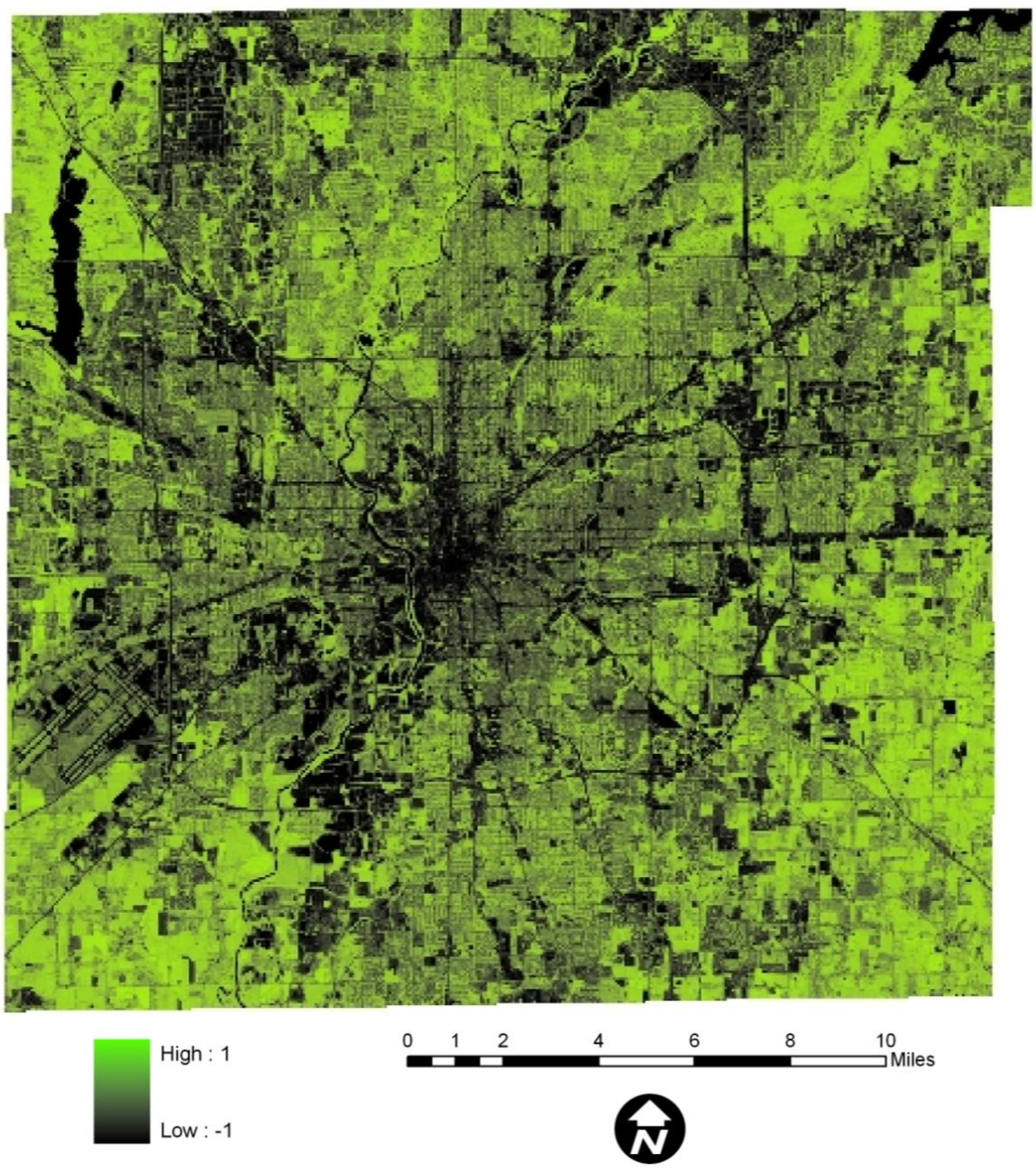
(1) Land-use mix = (-1)[(ft^2 residential / ft^2 residential, commercial, and office)ln(ft^2 residential / ft^2 residential, commercial, and office) + (ft^2 commercial / ft^2 residential, commercial, and office)ln(ft^2 commercial / ft^2 residential, commercial, and office) + (ft^2 office / ft^2 residential, commercial, and office)ln(ft^2 office / ft^2 residential, commercial, and office)] / ln(n3); where n3 = number of land-use types present.

The process by which this score was computed is described below. Residential, commercial, and office land-use polygons were selected from the aforementioned IMAGIS land-use dataset.

Normalized Difference Vegetation Index

Greenness may indicate the degree to which individual's surroundings are desirable places to spend time, which may in turn affect their physical activity levels (Frumkin 2001; Liu and Colbert *et al.* 2007). A vegetation index was used to evaluate the greenness of areas surrounding respondent locations. Indices use specific bands of the electromagnetic spectrum in remotely sensed imagery to identify a feature with which they are highly correlated. Birth and McVey (1968) defined the *Simple Ratio* as the visible red radiant flux divided by the near-infrared radiant flux (SR = ρ_{red} / ρ_{nir}). A variation of this index was put forth by Tucker *et al.* (1979) in the *Normalized Difference Vegetation Index* (NDVI), which standardizes value to a range from -1 to 1. Lower NDVI values represent absence of healthy vegetation (e.g., water or pavement) while higher values are indicative of healthy green vegetation (e.g., grass or forest) (NDVI = ρ_{nir} - ρ_{red} / ρ_{nir} + ρ_{red}). NDVI has been found to be inversely associated with the risk of overweight (Liu and Wilson *et al.* 2007). Time of year in which remotely sensed imagery is captured may affect the amount of information present in vegetation indices, with the mid- or late growing season offering more healthy plant canopies and green biomass for detection (Jensen 2005). NDVI here was derived from Landsat 5 Thematic Mapper imagery of the study area acquired May 4, 2004 using ERDAS Imagine 9.0.

Figure 3 – NDVI Image of Marion County, Indiana.



METHODS

Walkability Index

In order to measure net residential density and street connectivity, total land area within each spatial measure was estimated. Lakes, ponds, rivers, streams, and other water bodies were extracted from U.S. Fish and Wildlife Service National Wetlands Inventory data and U.S. Geological Survey National Hydrography data. The resulting layer was intersected with grid cells and census geographies in order to determine the water area and land area for each. The layer was converted to a ¼-meter resolution raster in order to calculate the amount of land area for Euclidian and network buffers using zonal analysis.

Net residential density was interpolated within grid cells through a series of vector layer intersections and summaries. First, residential land-use was selected from the IMAGIS land-use dataset (Step 1). The water layer described above was subtracted from the residential land-use (Step 2), where water bodies such as retention ponds coincided with the layer. The amount of residential land-use, without water, within census blocks was calculated using a census block boundary layer (Step 3). Densities of households in the blocks per residential land-use were then assigned to all land-use parcels according to the census blocks in which they were located (Step 4). In a few areas, land-use parcels were divided across block boundaries, in which case different residential densities were assigned to portions of the parcels. The resulting layer was then intersected with the grid, creating a new set of residential land-use polygons either falling inside grid cells or sharing edges with them (Step 5). Each was assigned the residential density of its respective polygon from Step 4. Grid cell household totals were calculated by multiplying each Step 5 polygon density by its area and adding all values within grid cells. The number of households was then divided by the total area of residential land-use within the grid cell to yield residential density. Net residential density was interpolated to Euclidian and network buffers by converting the residential land-use polygon layer with densities (from Step 4 above) to a 2½-meter resolution raster, multiplying each raster cell value by raster cell size to calculate household totals per cell, summarizing within each polygon for the number of households, and dividing by the residential area within the buffer (the number of residential pixels multiplied by the 2½-meter raster resolution scalar). Net residential density was developed for census block groups and census tracts by summarizing the amount of residential land-use in each geography (Steps 1 through 3 above), and dividing the block group or tract 2000 U.S. Census household count by the amount of residential land-use.

Street network connectivity was derived from the calculation of network dataset intersections with a valence greater than two per square mile of land area, as described above. Intersections were summarized using the ArcMap 9.2 Hawth's Analysis Tools extension, which includes a polygon point-count tool.

To derive land-use mix scores, area of land-use types were calculated for grid cells, census block groups, and census tracts by intersecting the three land-use type layers with the spatial measure boundaries and summarizing resulting polygons within each spatial measure. Areas of land-use types were computed for buffers by converting the three land-use type layers to ¼-meter resolution rasters and performing zonal analyses using each buffer type and distance. Frank *et al.*'s (2005) land-use mix score was calculated for all spatial measures using Equation 1. Water area was not subtracted from land-use types here as it was assumed that percentage of land area is less critical in determining the mix of designated land-use among the three selected types.

Walkability was determined for each spatial measure using Frank *et al.*’s (2005) walkability index:

(2) Walkability index = (6)(z-score of land-use mix) + (z-score of net residential density) + (z-score of street connectivity)

A normalized distribution was taken for residential density, street connectivity, and land-use mix to derive z-scores for each. Frank *et al*. (2005) reported that this arrangement of weights for components of the walkability index was the result of several trials and exhibited the most explanatory power for minutes of moderate physical activity per day.

Greenness

Greenness was measured using an NDVI index derived from a May 8, 2004 Landsat 5 Thematic Mapper image of the study area. Water features in the water layer described above were masked out of the image to address the possibility that some water, which exhibits characteristically low NDVI values, may represent appealing scenery or opportunities for physical activity. After masking, resulting low NDVI values could not be attributed to presence of water. The masked image was then summarized by zones using grid cells, Euclidian and network buffers, and census geographies to calculate the mean NDVI values for each respondent for each spatial measure method.

Analysis

We performed student’s t-tests assuming unequal variances to test for statistically significant differences ($p<0.05$) among the nine different methods and distances (Table 1) when measuring walkability and NDVI. We also tested each component of Frank *et al.*’s (2005) walkability index individually: residential density, street connectivity, and land-use mix. T-tests excluded edge residents (N=548) and respondent locations geocoded to points other than known intersections due to inaccurate or missing intersection data (N=493). Remaining respondents totaled 3,771, or 79.0% of the total geocoded survey dataset. Tests for significant differences in walkability and greenness were performed for this respondent selection. Statistical analyses were also conducted comparing racial groups, and comparing those respondents meeting the U.S. Department of Health and Human Services (DHHS) recommendation for walking to reduce risk of chronic disease (30 minutes of moderate-intensity activity a day, five days a week) versus those not meeting the DHHS recommendation.

We also examined relationships between environmental variables (walkability z-score and NDVI) and self-reported amount of time walking per day, in minutes. The survey questions were worded as follows:

> "Now think about the time you spent walking in the last 7 days. This includes at work and at home, walking to travel from place to place, and any other walking you might do solely for recreation, sport, exercise, or leisure. During the last 7 days, on how many days did you walk for at least 10 minutes at a time? How much time did you usually spend walking on one of those days?" (Marion County Health Department, 2005)

Bivariate and multiple logistic regressions were performed for each of the nine methods and distances, both unadjusted and adjusted for individual-level sociodemographic variables: gender, age, race/ethnicity, educational attainment, and household income as a percent of the federal poverty level. Sociodemographic variables were included in regressions using the following categories for age: (1) 18-34, (2) 35-44, (3) 45-64, and (4) 65-96; for race/ethnicity: (1) white non-Latino, (2) Black non-Latino, (3) Latino, and (4) other or missing; educational attainment: (1) grades 0-11, (2) high school diploma or GED, (3) 1-3 years of college, and (4) 4+ years of college; and household income: (1)

below 200% of the federal poverty level and (2) equal to or above 200% of the federal poverty level. Regressions were performed including and excluding respondent locations geocoded to points other than known intersections (N=493).

In order to test for non-linear relationships between environmental variables and walking, models were constructed to include walkability and NDVI as categorical variables representing quartile ranges. The dependent variable was categorized as a bivariate outcome using seven different stratifications: (1) walks at least 3 days a week for 10 minutes a day, (2) at least 3 days a week for 30 minutes a day, (3) at least 5 days a week for 10 minutes a day, (4) at least 5 days a week for 30 minutes a day (U.S. DHHS recommendation to reduce risk of chronic disease), (5) at least 7 days a week for 10 minutes a day, (6) at least 7 days a week for 30 minutes a day, and (7) at least 7 days a week for 120 minutes a day.

Logistic regressions were informed by tests for spatial autocorrelation, which can be present in the geographic distribution of any phenomenon (Cliff and Ord 1973). Spatial autocorrelation in the amounts of walking would be present where respondents who live close to others with similar behavior patterns exhibit similar frequency of walking. Such conditions violate the assumption of independence fundamental to most statistical analyses, and spatially autocorrelated observations offer less information than independent variates (Cliff and Ord 1975). A search of the literature on analysis of built environmental variables and associations with health outcomes did not reveal previous consideration of spatial autocorrelation.

Self-reported walking data were tested using the Spatial Autocorrelation tool within ArcMap 9.2, which uses a global or local Moran's *I* statistic (1948). Settings used in spatial autocorrelation tests included inverse distance effect of one variable on another, inverse distance-squared effect, and global, 2-kilometer search distance, and 400-meter search distance settings. Tests were performed on raw self-reported walking data *x*, log(*x*), walking data classified by quantiles, and walking data classified by U.S. DHHS physical activity recommendations (http://www.health.gov/dietaryguidelines/dga2005/document/). Autocorrelation in spatial distribution of minutes walking per day did not approach significance (p=.05) in any test (see Table 2 – Tests for Spatial Autocorrelation).

Table 2 – Tests for Spatial Autocorrelation.

			Moran's Index	Expected Index	Variance	Z-score	p-value
Raw Data	Global	Inverse Dist.	0.012787	-0.000210	0.000207	0.904125	0.182965
		Inverse Dist.^{2}	0.073129	-0.000210	0.024652	0.467091	0.320217
	2-km	Inverse Dist.	0.030124	-0.000210	0.001243	0.860517	0.194752
		Inverse Dist.^{2}	0.073145	-0.000210	0.024664	0.467086	0.320219
	400-m	Inverse Dist.	0.034967	-0.000210	0.001965	0.793523	0.213737
		Inverse Dist.^{2}	0.073158	-0.000210	0.024675	0.467067	0.320225
log(raw data)	Global	Inverse Dist.	0.009699	-0.000210	0.000207	0.688322	0.245625
		Inverse Dist.^{2}	0.076799	-0.000210	0.024724	0.489754	0.312154
	2-km	Inverse Dist.	0.021975	-0.000210	0.001246	0.628436	0.264859
		Inverse Dist.^{2}	0.076816	-0.000210	0.024736	0.489747	0.312156
	400-m	Inverse Dist.	0.023248	-0.000210	0.001971	0.528385	0.298616
		Inverse Dist.^{2}	0.076829	-0.000210	0.024747	0.489718	0.312167
Quantiles*	Global	Inverse Dist.	0.011313	-0.000210	0.000207	0.800484	0.211715
		Inverse Dist.^{2}	0.058353	-0.000210	0.024722	0.372458	0.354776
	2-km	Inverse Dist.	0.025553	-0.000210	0.001246	0.729822	0.232749
		Inverse Dist.^{2}	0.058365	-0.000210	0.024734	0.372450	0.354778
	400-m	Inverse Dist.	0.027129	-0.000210	0.001971	0.615842	0.268999
		Inverse Dist.^{2}	0.058374	-0.000210	0.024745	0.372418	0.354790
USDHHS[†] Recommendation	Global	Inverse Dist.	0.014530	-0.000210	0.000207	1.023994	0.152919
		Inverse Dist.^{2}	0.104297	-0.000210	0.024718	0.664720	0.253115
	2-km	Inverse Dist.	0.034046	-0.000210	0.001246	0.970484	0.165903
		Inverse Dist.^{2}	0.104320	-0.000210	0.024729	0.664714	0.253117
	400-m	Inverse Dist.	0.038601	-0.000210	0.001970	0.874348	0.190964
		Inverse Dist.^{2}	0.104340	-0.000210	0.024740	0.664686	0.253125
USDHHS[††] Recommendation	Global	Inverse Dist.	0.012545	-0.000210	0.000207	0.886061	0.187792
		Inverse Dist.^{2}	0.088694	-0.000210	0.024722	0.565426	0.285892
	2-km	Inverse Dist.	0.029103	-0.000210	0.001246	0.830367	0.203166
		Inverse Dist.^{2}	0.088714	-0.000210	0.024734	0.565420	0.285894
	400-m	Inverse Dist.	0.031909	-0.000210	0.001971	0.723507	0.234684
		Inverse Dist.^{2}	0.088729	-0.000210	0.024745	0.565389	0.285904

* 0 = 0 min/day, 1 = 1-18 min, 2 = 20-25 min, 3 = 40-45 min, 4 = 47-105 min, 5 = 120+ min
† 0 = 0 min/day, 1 = 1-29 min, 2 = 30-59 min (to reduce risk of chronic disease), 3 = 60-90 min (to help manage body weight or to sustain weight loss), 4 = 91+ min
†† 0 = 0 min/day, 1 = less than 30 min, 2 = 30+ min

RESULTS

The majority of respondents were white non-Latinos (65.1%) between the ages of 25 and 54 (61.9%), were high school graduates (84.2%) and had some college education (54.4%), and had incomes over 300% of the federal poverty level (55.7%).

Table 3 – Study Population Characteristics

	Marion County Adult Obesity Survey	Marion County (U.S. Census, 2005)
% Adults Female	51.8	52.4
% White non-Latino	69.4	65.1
% Black non-Latino	23.8	24.8
% Latino	4.5	6.0
% Adults 18-24	8.4	11.0
% Adults 25-34	24.6	20.6
% Adults 35-44	21.9	21.5
% Adults 45-54	16.3	19.8
% Adults 55-64	13.7	12.5
% Adults 65-74	7.9	7.6
% Adults 75+	7.2	7.0
% Adults Below 100% Federal Poverty Level	6.3	14.8
% Adults 100-199% Federal Poverty Level	15.1	19.8
% Adults 200-299% Federal Poverty Level	17.1	17.4
% Adults Above 300% Federal Poverty Level	61.5	48.0
% No High School Degree	8.7	15.8
% High School Degree	28.3	29.8
% Some College	25.7	21.1
% College Graduate	37.3	33.3

Differences were observed in the relationships between mean, range, and standard deviation of the walkability index, its components, and greenness by size and method of spatial measure. Mean values for residential density and street connectivity decreased as the size of the analytic area increased. Range of values and standard deviation for these variables also decreased with area. Land-use mix displayed a less linear relationship with size of spatial measure method. Both mean values and range of land-use mix were lowest using census block groups and tracts. Mean values were highest using 2-kilometer buffers of both types and range of values was highest using 400-meter buffers of both types. Standard deviation of land-use mix consistently decreased as size of spatial measure method increased.

As the walkability index was composed of z-scores, mean values were near zero for all respondent-based measure methods, higher for grid cells (2.189) and lower for census block groups and tracts (-0.114 and -0.736, respectively). Range and standard deviation of walkability z-scores tended to increase with size of spatial measure method. Mean values of NDVI increased with size of spatial measure method, while range and standard deviation of those values decreased (Table 4).

Table 4 – Descriptive Statistics.

		400m Network n=3771	400m Euclidian n=3771	Grid n=3771	1km Network n=3771	Block Group n=3771	1km Euclidian n=3771	Tract n=3771	2km Network n=3771	2km Euclidian n=3771
Walkability	Mean	0.0000	0.0000	2.1885	0.0000	-0.1140	0.0000	-0.7357	0.0000	0.0000
	Min	-9.7861	-10.5794	-8.6905	-12.3649	-9.1833	-12.9948	-11.9301	-15.6299	-17.5959
	Max	23.2244	26.8529	32.8018	27.5056	26.8731	28.6795	27.4482	26.8556	29.1253
	SD	6.4390	6.5888	6.7273	6.8007	6.2003	6.9227	6.5979	7.0163	7.1316
Residential Density	Mean	5.7424	5.7112	5.5900	5.2785	**5.9611**	5.1466	5.2658	4.9488	**4.7840**
	Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.2053	0.0000	0.1555	0.2438
	Max	221.4745	85.7724	77.7439	58.5044	150.4357	41.8202	46.7423	29.5347	25.7444
	SD	8.4592	5.2808	5.2382	4.0888	9.1311	3.6590	4.6134	3.1538	2.7533
Street Connectivity	Mean	**41.7831**	36.1346	35.2849	37.7003	34.7248	34.2081	32.8122	35.1346	**32.0530**
	Min	0.0000	0.0000	0.0000	0.9111	2.5055	0.6508	4.0847	1.1371	1.5480
	Max	209.4083	171.0915	131.1678	138.6528	195.8265	117.4563	108.1984	88.3056	74.4704
	SD	24.0362	19.1968	18.3441	16.0339	19.5020	13.4938	15.0896	12.0074	10.2790
Land Use Mix	Mean	0.3759	0.3836	0.3765	0.3925	**0.3375**	0.3790	0.3703	0.4140	**0.4140**
	Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Max	0.9989	0.9989	0.9966	0.9991	0.9863	0.9978	0.9773	0.9918	0.9921
	SD	0.3060	0.3023	0.2945	0.2644	0.2513	0.2455	0.2217	0.2185	0.1903
NDVI	Mean	**0.3252**	0.3433	0.3522	0.3617	0.3696	0.3728	0.3725	0.3703	**0.3739**
	Min	0.0166	-0.0016	-0.0066	0.0488	-0.0138	0.0630	0.0512	0.1087	0.1216
	Max	0.6231	0.6135	0.6420	0.5874	0.6177	0.5988	0.5759	0.5908	0.5728
	SD	0.1156	0.1047	0.1024	0.0910	0.0944	0.0846	0.0831	0.0776	0.0720

In the relationships observed between descriptive statistics of environmental variables and size of analytic area, use of census block groups and census tracts frequently resulted in greater variability (Tables 4a-b).

Figure 4a – Mean Walkability Indices.

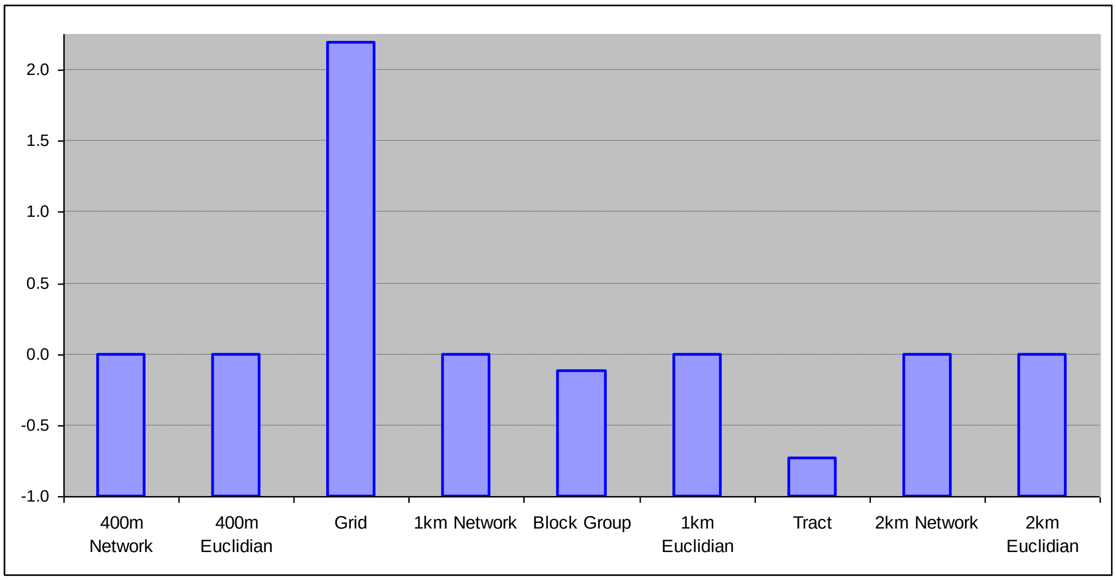
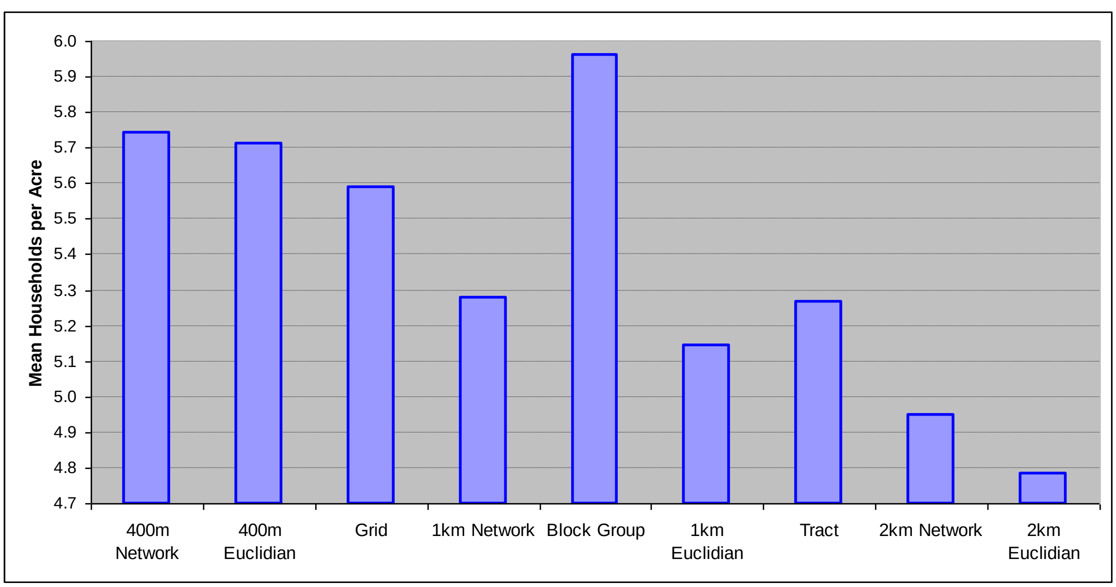


Figure 4b – Mean Residential Density.



In pairwise t-tests of residential density using all spatial measure methods, eight of thirty-six pairs were not statistically different (Table 5). Of these eight, six involved grid cells, census block groups, or census tracts. All other pairs were significantly different ($p<0.05$). In t-tests of street connectivity among all spatial measure methods, only four pairs were not significantly different, each of these including either grid cells or census block groups (Table 6). Tests of significant difference among the methods of measuring land-use mix were more often not statistically significant: such was the case in eleven of thirty-six comparisons (Table 7).

Table 5 – T-tests for Residential Density.

	400m Net	400m Euc	Grid Cell	1km Net	Block Group	1km Euc	Tract	2km Net	2km Euc
400m Net									
400m Euc	ns								
Grid Cell	ns	ns							
1km Net	0.0024	0.0001	0.0040						
Block Group	ns	ns	0.0305	0.0000					
1km Euc	0.0001	0.0000	0.0000	ns	0.0000				
Tract	0.0024	0.0001	0.0044	ns	0.0000	ns			
2km Net	0.0000	0.0000	0.0000	0.0001	0.0000	0.0119	0.0005		
2km Euc	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0157	

ns: not significant (p>=0.05)

Table 6 – T-tests for Street Connectivity.

	400m Net	400m Euc	Grid Cell	1km Net	Block Group	1km Euc	Tract	2km Net	2km Euc
400m Net									
400m Euc	0.0000								
Grid Cell	0.0000	0.0495							
1km Net	0.0000	0.0001	0.0000						
Block Group	0.0000	0.0016	ns	0.0000					
1km Euc	0.0000	0.0000	0.0037	0.0000	ns				
Tract	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
2km Net	0.0000	0.0067	ns	0.0000	ns	0.0016	0.0000		
2km Euc	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0107	0.0000	

ns: not significant (p>=0.05)

Table 7 – T-tests for Land-use Mix.

	400m Net	400m Euc	Grid Cell	1km Net	Block Group	1km Euc	Tract	2km Net	2km Euc
400m Net									
400m Euc	ns								
Grid Cell	ns	ns							
1km Net	0.0115	ns	0.0131						
Block Group	0.0000	0.0000	0.0000	0.0000					
1km Euc	ns	ns	ns	0.0216	0.0000				
Tract	ns	0.0284	ns	0.0001	0.0000	ns			
2km Net	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000		
2km Euc	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	ns	

ns: not significant (p>=0.05)

Tests of significant difference among all spatial measure methods for the walkability index showed differences only where grid cells or census tracts were compared to other methods (Table 8). T-test results were the same when stratifying by race (Black non-Latino or white non-Latino) or physical activity (met U.S. DHHS recommendation to maintain health and reduce risk for chronic disease or did not). These results should be considered noting that mean walkability indices for all respondent-based measure methods were near zero, whereas mean indices for grid cells and census geographies among respondents varied.

Table 8 – T-tests for Walkability Indices.

	400m Net	400m Euc	Grid Cell	1km Net	Block Group	1km Euc	Tract	2km Net	2km Euc
400m Net									
400m Euc	ns								
Grid Cell	0.0000	0.0000							
1km Net	ns	ns	0.0000						
Block Group	ns	ns	0.0000	ns					
1km Euc	ns	ns	0.0000	ns	ns				
Tract	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
2km Net	ns	ns	0.0000	ns	ns	ns	0.0000		
2km Euc	ns	ns	0.0000	ns	ns	ns	0.0000	ns	

ns: not significant (p>=0.05)

T-tests for NDVI among all pairs of spatial measure methods resulted in no significant differences for eight of thirty-six pairs (Table 9). These eight were comparisons among larger analytic zones (census block groups, 1-kilometer Euclidian buffers, census tracts, and 2-kilometer network and Euclidian buffers). Results were similar when stratifying by race and U.S. DHHS physical activity recommendation, as in tests described above.

Table 9 – T-tests for NDVI.

	400m Net	400m Euc	Grid Cell	1km Net	Block Group	1km Euc	Tract	2km Net	2km Euc
400m Net									
400m Euc	0.0000								
Grid Cell	0.0000	0.0002							
1km Net	0.0000	0.0000	0.0000						
Block Group	0.0000	0.0000	0.0000	0.0002					
1km Euc	0.0000	0.0000	0.0000	0.0000	ns				
Tract	0.0000	0.0000	0.0000	0.0000	ns	ns			
2km Net	0.0000	0.0000	0.0000	0.0000	ns	ns	ns		
2km Euc	0.0000	0.0000	0.0000	0.0000	0.0252	ns	ns	0.0361	

ns: not significant (p>=0.05)

In logistic regressions, no significant relationship was found between the walkability z-score and reported amount of walking for any walking outcome stratification. A significant negative relationship between NDVI and walking was found using each of the different thresholds for defining the walking outcome variable. The only spatial measure method consistently producing this significant negative relationship across each stratification was census tract. In bivariate models using several different spatial measure methods, NDVI had a significant ($p<0.10$) and negative relationship with walking. NDVI was not significantly associated with walking in multivariate models that controlled for sociodemographic variables. Census tract NDVI was significantly ($p<0.05$)

and negatively associated with walking in both bivariate and multivariate models for second and third NDVI quartiles. A summary of the results from the logistic regression analyses is provided in Table 10.

Table 10 – Selected Results from Regressions.

Outcome:	**Walks at least 3 days a week for 10 minutes**		
	Walkability:	No significant relationships found	
	NDVI:	**Negative** relationship	
		2km Network Buffer	(2nd quartile)
		Census Tract	(2nd quartile)
Outcome:	**Walks at least 3 days a week for 30 minutes**		
	Walkability:	No significant relationships found	
	NDVI:	**Negative** relationship	
		1km Network Buffer	(3rd quartile)
		Census Tract	(3rd quartile)
Outcome:	**Walks at least 5 days a week for 10 minutes**		
	Walkability:	No significant relationships found when including confounding variables	
	NDVI:	**Negative** relationship	
		1km Euclidian Buffer	(3rd quartile)
		Census Tract	(3rd quartile)
Outcome:	**Walks at least 5 days a week for 30 minutes**		
	Walkability:	No significant relationships found when including confounding variables	
	NDVI:	**Negative** relationship	
		Census Tract	(3rd quartile)
Outcome:	**Walks at least 7 days a week for 10 minutes**		
	Walkability:	No significant relationships found	
	NDVI:	**Negative** relationship	
		Census Tract	(2nd quartile)
		Census Tract	(3rd quartile)
Outcome:	**Walks at least 7 days a week for 30 minutes**		
	Walkability:	No significant relationships found	
	NDVI:	**Negative** relationship	
		400m Euclidian Buffer	(3rd quartile)
		Census Tract	(3rd quartile)
Outcome:	**Walks at least 7 days a week for 120 minutes**		
	Walkability:	No significant relationships found when including confounding variables	
	NDVI:	**Negative** relationship	
		Census Tract	(2nd quartile)
		Census Tract	(3rd quartile)

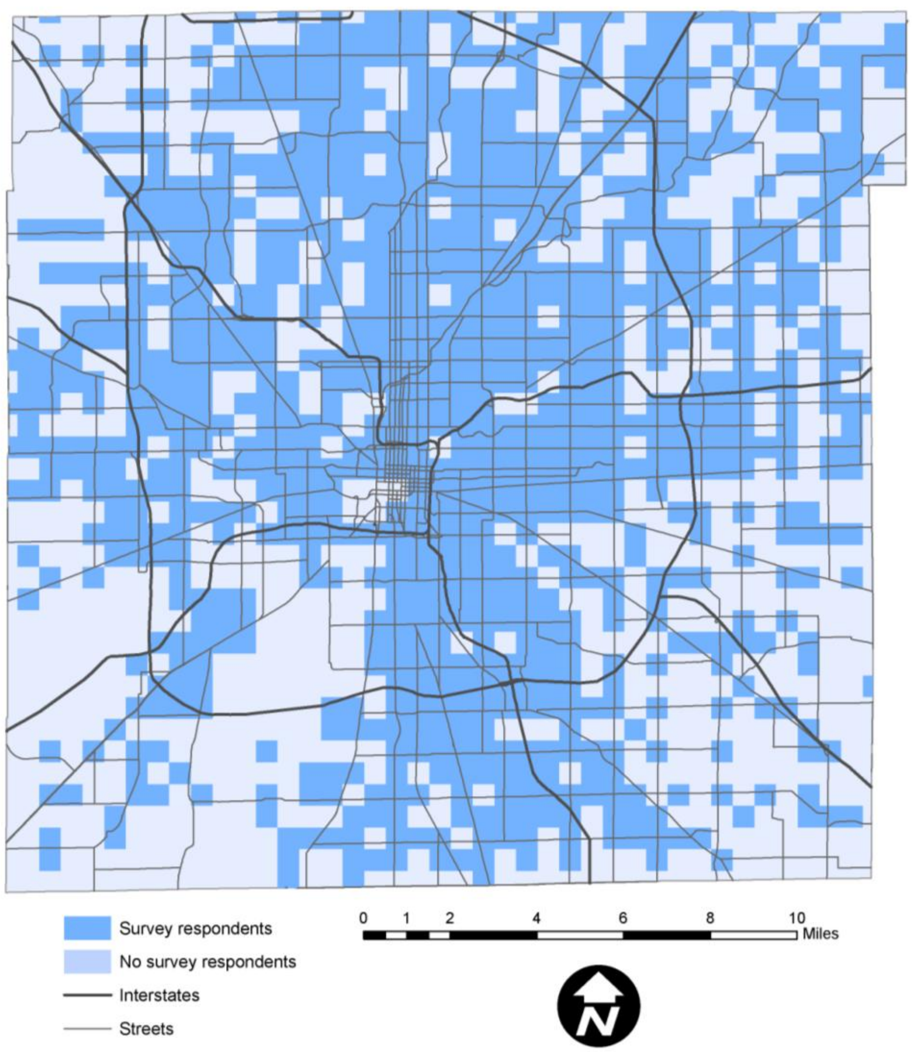
DISCUSSION

Given the range of previous methods and findings in the literature, we designed the current study to compare the relevance of previously used forms (grid cells, Euclidian and network buffers, and census geographies) and previously used distances (400-meter, 1-kilometer, and 2-kilometer buffers; 805-meter square grid cells) in examining associations of the built environment and health. As a basis for the comparison, we chose to test transferability to Marion County, Indiana of Frank *et al.*'s (2005) previously established model using combined measures of urban form and sociodemographics to predict moderate physical activity in the Atlanta metropolitan area. This and previous work offer a growing body of evidence of effects of the built environment on physical activity (King *et al.* 2000; Brownson *et al.* 2001; Pikora *et al.* 2003; Hoehner *et al.* 2005; Frank *et al.* 2005). Frank *et al.*'s (2005) study combined measures of residential density, street connectivity, and land-use mix into a walkability index, which was positively associated with the number of minutes walked per day collected via accelerometer. A previous study examining impact of objectively measured land-use variables on *self-reported* walking activity from telephone survey data, as we present here, found significant relationships between the types of land-use surrounding residences of a sample of adults in El Paso, Texas (Rutt and Coleman 2005). In addition to calculating the walkability index scores for our study area, we also measured and tested effects of a vegetation index on walking. Greenness has been suggested as beneficial in a range of health and behavior concerns including psychological development among children (Faber Taylor, Kuo, and Sullivan 2002; Faber Taylor and Kuo 2006), mitigating psychological factors leading to aggression and crime (Kuo and Sullivan 2001), and improving attentional functioning among children with attention-deficit/hyperactivity disorder (Faber Taylor, Kuo, and Sullivan 2001; Kuo and Faber Taylor 2004). Additionally, Liu and Colbert *et al.* (2007) found greenness measured using the Normalized Difference Vegetation Index in May 8, 2001 Landsat Enhanced Thematic Mapper Plus imagery to be positively correlated with children's perceptions of neighborhood walkability. These findings suggest the appropriateness of the inclusion of greenness in the model predicting the amount of time spent walking.

Results of measurement of environmental variables using multiple forms and distances have been previously presented (e.g., two different buffer radii, Moudon *et al.* 2006; three different buffer radii, Berke *et al.* 2007; two different buffer types, Oliver, Schuurman, and Hall 2007), and reviews of health research using objective measures of the built environment have been presented (Papas *et al.* 2007) . However, no studies were found specifically discussing comparisons of characteristics of the built environment using several different analytic forms *and* distances. Limitations in using a narrow selection of search distances to measure variables of the built environment with GIS operations have been recognized (Saelens *et al.* 2003; Liu and Colbert *et al.* 2007; Bell, Liu, and Wilson 2008) and the need for further work towards appropriate theory-based measurement methods has been stressed (Diez Roux 2001; Allacci 2005). This study compares results using nine spatial measure methods and distances (Table 1) in predicting self-reported amount of time walked by survey respondents, whereas other studies have examined effects of the built environment in health using body mass index data, a potentially more confounded relationship (Burdette and Whitaker 2003; Eid *et al.* 2006; Ewing, Brownson, and Berrigan 2006; Mobley *et al.* 2006).

This study is notable for a survey design that enabled post-stratification weighting such that respondents were representative of the racial composition of Marion County, Indiana. Benefits of a representative sample include generalizability of results to the study area population. The spatial distribution of the sample was also geographically representative of a large Midwestern city (Metropolitan Statistical Area population 1,607,496; U.S. Census Bureau, 2006) with respondent points located throughout both the urban core and outer more suburban townships (see Figure 4).

Figure 5 – Distribution of Respondents by Grid Cells.



Limitations of this study include the use of self-reported physical activity data. Time walked per day was widely reported in 10- or 15-minute increments and could not be treated as a continuous variable in the analysis. Survey questions regarding the amount of time walked did not differentiate between walking in different contexts, such as at work or at home. Analysis here focused on the immediate residential environment, which represents only part of the potential contextual impact on walking reported in the survey. Wiehe *et al.* (2007) stress the importance of capturing an individual's contextual exposure throughout space and time in order to thoroughly examine environmental impact in health research. In light of limitations of self-reported data, objective readings of physical activity using accelerometers have also been used to analyze physical activity (Frank *et al.* 2005; Cohen *et al.* 2006; Norman *et al.* 2006).

Other limitations of this study were related to geocoding methods necessitated by the nature of respondent residence information included in the survey data. Self-reported approximate location of residence, referencing an intersection, could introduce a range of distances from geocoded points to actual respondent residence locations. While some respondents may accurately report the nearest existing intersection, others may report a more distant intersection of major thoroughfares. In areas with less dense street networks such as the northwestern and southeastern corners of the study area (Figure 5), nearest intersections may be as far as one kilometer from the location of residence.

Respondent locations centered on large, high-traffic intersections could also affect the relationships between environmental measurements and spatial measure method and distance. In comparison of different methods of measuring NDVI at each respondent location, values increased with the size of spatial measure method, implying less greenness captured at smaller distances where pavement and buildings were likely to occupy a greater proportion of the land cover. When measuring street connectivity, values decreased with size of spatial measure, which might indicate geocoding bias towards areas with higher intersection density. Proximity of the reported intersection to actual respondent residence could vary according to willingness or ability to report street names. A total of 493 respondents (10.3%) were geocoded to a point other than a known intersection due to incomplete or inaccurate intersection information. These instances could also be related to respondents' willingness or ability to report residential information. Additionally, these respondents were more likely to be high-minority and low-income compared to all respondents (analyses not presented but available on request). This finding could impact the utility of survey data geocoded using these same methods where geographical analysis requires exclusion of such points.

Implications of Comparisons

Residential density was considerably higher when measured using census block groups and land-use mix was considerably lower compared to 1-kilometer network or Euclidian buffers (measures of roughly similar area to census block groups). As census block groups are most often bounded by major thoroughfares, zoning patterns could possibly be coincident with block group boundaries. More residential area could be encompassed within block groups resulting in higher residential density, or fewer types or land-use or less mix of land-use types could be present.

Two components of the walkability index, residential density and street connectivity, displayed negative relationships with size of spatial measure method. This pattern could be attributed to the urban form of Marion County, with a central city core and outlying suburban or rural areas. Where analytic zones are increased in size, analyses are more likely to include outlying areas which are less densely populated and have less dense street networks.

There were few significant differences in measures of land-use mix across the nine methods. It should be noted that Frank *et al.*'s (2005) walkability index formula weighted land-use mix six times greater than residential density or street connectivity. Frank *et al.*'s (2005) arrangement of weights, given the relative lack of significant differences of land-use mix measure methods, could contribute to the finding that all pair-wise t-tests for differences among the nine measure methods of walkability were not significantly different except for grid cells and census tracts, which are not respondent-based z-scores and therefore result in mean z-scores less than or greater than zero for index components. Furthermore, Frank *et al.*'s (2005) study area consisted of the 13-county Atlanta metropolitan area, which potentially represents a far greater range of land-use mix measured at subject locations than in our one-county study area.

In measurements of NDVI, pairs of relatively large measure methods did not show significant differences (e.g., 2-kilometer network or Euclidian buffers) whereas two smaller methods *were* significantly different. The results could signal, in part, effects of the geocoding methods used for respondent data. Where NDVI is lowest, at larger geographic scales for intersection-geocoded points, slight variations in size or type of measure may capture significantly different amounts of greenness. Conversely, at smaller scales, particularly among census block groups, tracts, 1-kilometer Euclidian buffers, or 2-kilometer buffers, differences in greenness were not significant. Aside from interactions with geocoding bias, NDVI may be distributed in urban regions such that substantial variability occurs across small distances. For example, small “pockets” of vegetation may be more frequently interspersed alongside built environment elements that are much less green compared to suburban areas where there may be larger swaths of greenness.

Implications of Regressions

Among several logistic regressions using varying stratifications of minutes walked per week, the walkability index was not significantly associated with amount of time spent walking. Given these results, the construction of the walkability formula might need to be more appropriately tailored to a large Midwestern city. Justification for the weighting of land-use mix in Frank *et al.*’s (2005) formula could be found in earlier work by Frank, Andresen, and Schmid (2004), also conducted in the Atlanta metropolitan area, in which mixed land-use exhibited the strongest and negative association with body mass index compared to the other two components. This work was informed by previous findings that land-use mix is positively associated with utilitarian walking (Frank and Pivo 1995; Handy 1996; Saelens, Sallis, and Frank 2003; Sallis *et al.* 2004). More recent work by Frank *et al.* (2006) modified the walkability index to include retail floor area ratio (retail building floor area divided by retail land-use area) and found walkability to be significantly positively associated with active transportation and negatively associated with body mass index in King County, Washington. However, in following work by Kerr *et al.* (2006), the same walkability index was found to have no effect on active transportation to school among children in low-income areas of King County. Frank *et al.* (2005, 2006) used 1-kilometer network buffers to measure walkability while Kerr *et al.* (2006) used census block groups.

McCormack *et al.* (2006) caution that indices assessing built environment supportiveness of walking should be examined for validity before being widely applied in research on environmental correlates with physical activity. Tests of Indianapolis area residential density, street connectivity, and land-use for associations with physical activity or weight status might reveal different degrees of import than those found in the Atlanta and Seattle areas and thus justify further reassessment. Presence of and condition of sidewalks, crime levels, traffic levels, and qualitative data such as perceptions of safety could also contribute to a more widely applicable, robust walkability metric.

A positive association of greenness with amount of walking per week was found when measured using 2-kilometer Euclidian buffers and stratifying by high and low residential density (above / equal to vs. below 4.32 households per acre of residential land-use). This association was statistically significant ($p<0.05$) in areas of low residential density and borderline significant ($p<0.10$) in high-density areas. In regressions not stratified by residential density, greenness exhibited a negative relationship with walking. Given that areas of high residential density tend to have lower NDVI and many high density areas in our study were also low-income areas, a greater amount of utilitarian walking may have been reported in these areas such that the hypothesized positive effect of greenness was not evident when analyzing the study group as a whole. Respondents in high-density areas walked, on average, 453 minutes per week compared to respondents in low-density areas who walked 413 minutes per week. This is consistent with previous findings that children in Marion County in low-income neighborhoods with low NDVI report higher levels of physical activity (Liu and Colbert *et al.* 2007). Census tracts may be representative of this sociodemographic segregation given consistent findings of this negative relationship across several walking outcome thresholds (Table 10).

Further Considerations for Spatial Measure Methods

While considering the varying outcomes of different sizes of analytical zones in assessing environmental exposure for health research, one should also consider techniques beyond using multiple buffer sizes. Zandbergen and Chakraborty (2007) have underlined and expanded one of the principal findings of spatial measure method comparisons here: that different buffer distances produce different results. They suggest that in measuring environmental exposure, one cannot regard any one buffer size as more relevant than another and that the discreet boundaries of buffers do not allow for the effect of distance beyond this arbitrary line. They propose cumulative distribution functions (CDFs) as alternatives to buffers, census geographies, or proximity comparison, specifically in assessment of exposure to pollution sources and health risks among school-aged children in Orange County, Florida (Zandbergen and Chakraborty 2007). Given the complex and, in some instances, conflicting array of measurement methods found in the literature on built environmental effects on health, researchers should remain open to methods such as CDFs, which may lack the familiarity or statistical straightforwardness of other more common approaches.

As suggested above in discussion of walkability indices, future decisions regarding appropriate spatial measure methods or distances might also be improved by consideration of qualitative data. Several hypotheses have emerged from the literature suggesting effects of the built environment on health outcomes, often using the term "neighborhood." Perceptions of neighborhood may help define the spatial extent to which people interact with the environment. Diez Roux (2001) suggests, "…neighborhoods defined on the basis of people's perceptions may be relevant when the neighborhood characteristics of interest relate to social interactions or social cohesion…" (p. 1785). Examining resident-drawn maps of neighborhoods, Coulton *et al.* (2001) found differences between resident-defined neighborhood boundaries and census block group and tract boundaries. As a result, the authors also noted differences in sociodemographic descriptors within these differently defined boundaries, suggesting potential bias where census units are used to define neighborhood. These and other inquiries in the concept of neighborhood (Young, Russell, and Powers 2004; Moudon *et al.* 2006; Pearce, Witten, and Bartie 2006) warrant further consideration of the social nature of individual elements of the built environment, how they relate to concepts of neighborhood, and how they might be better spatially investigated.

Hypotheses of the active living movement suggesting environmental interventions in physical activity and other health-related outcomes might also be better informed by a critical social justice perspective. Day (2006) suggests that proposed changes to urban and suburban form are not blanket solutions to health concerns and, in their most rudimentary form, sometimes advocate a simple replication of older urban core design while ignoring possible non-planning related solutions to health concerns in low-income minority communities. Day (2006) mentions, "…many older urban environments boast an impressive array of the very features that are hypothesized to support active living: grid street patterns that increase connectivity, high densities, public transportation, and sidewalks" (p. 92), while also stressing urban low-income Black and Latino populations experience the greatest risks for overweight and obesity. Insofar as analyses of the built environment are relevant and beneficial for these populations, how might measurement methods be adjusted given problematizations of developing active living theories? Street-based or modified Euclidian buffers might be re-designed to more accurately emphasize areas of potential pedestrian activity (street sides), de-emphasize other areas (building footprints, enclosed areas), and re-evaluate detractors (absent sidewalks, high-crime areas). Such reassessments could be incorporated into widely-used software methods for generating buffers.

Limitations of this study included residence-based analyses using self-reported walking data that did not differentiate between place or time of day of physical activity. Researchers have proposed (Kwan 2002, 2004) and implemented (Mackett *et al.* 2006, 2007; Wiehe *et al.* 2007) methods for recording and analyzing space-time paths for social science and health research. In a recent study, Shoval and Isaacson (2006) review and compare accuracy of GPS and time difference of arrival systems in collecting data on pedestrian movement. The authors suggest that given continual improvements in technologies, research involving movement through space and time will soon achieve levels of accuracy that allow investigators to move beyond data limitations and focus on analysis techniques. Researchers have also considered travel speed and mobility in urban environments when constructing appropriate areas of environmental context (Kwan 2004). Kwan (2004) stresses the role of travel speed along urban transportation networks and incorporates this element in her delineation of “Potential Path Areas” of study subjects. Given these innovations and impending advances, buffers or other spatial analysis instruments will be able to be adjusted accordingly in order to capture a more detailed and comprehensive picture of environmental exposure of study subjects.

CONCLUSION

In this study, results of measuring walkability and greenness using nine spatial measure methods and distances are presented, compared, and tested for significant difference. Additionally, results of using each of these methods in testing walkability and greenness as correlates of walking among adults are presented. This work emphasizes that size and type of geographic method significantly influences results of measurements and may have important implications for how these variables perform in analytic models of health behavior. Residential density and street connectivity exhibited decreased means with larger analytic zones, while NDVI showed increased means. Residential density, street connectivity, land-use mix, and NDVI each exhibited decreased variability as size of analytic zone increased, whereas the walkability index increased in variability. Census geographies, widely used in the public health literature in investigating effects of the environment (Diez Roux 2001), varied from the relationships described above in all measurements. Administrative boundaries such as zip-codes, census tracts, and block groups, despite obvious advantages over individual-level geographies in data availability, might be reconsidered as standards in geographic health research. As Diez Roux (2001) suggests, use of such methods might be best applied in investigation of policy or those geographic phenomena with inherent ties to the boundaries.

In addition to varied patterns in measurements, statistically significant differences between spatial measure methods and distances in Marion County were observed for residential density, street connectivity, land-use mix, and NDVI. The walkability index as formulated in Frank *et al*. (2005) largely showed no significant differences among the nine methods and distances compared. These results suggest the explanatory power of the index is not transferable to Marion County, Indiana.

NDVI *did* emerge as a significant predictor of physical activity using seven different stratifications of minutes walked per week. Greenness was significantly negatively related to walking in each regression, but this finding was consistent only when measured using census tracts. Stratifying this analysis by low/high residential density changed the direction of the relationship; for respondents in low-residential density areas, the relationship was significant and positive.

Each of the above findings, in addition to further and more inclusive comparisons of types of spatial measure methods and distances, should serve to inform future decisions in geographic analysis for health research examining the built environment. As put forth by Allacci (2005), researchers should consider the selection of geographic methods and scales as integral in the process of analysis of effects of environment. Most crucially, future work investigating effects of the environment on health should consider the nature of each geographic phenomenon in question - physical, social, administrative, and otherwise - with a critical perspective in order to move towards a standard based in more than frequency or familiarity of common approaches.

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